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LOCALIZATION OF EPILEPTIC FOCI FROM IEEG VIA MIXED CONVOLUTIONAL NEURAL NETWORK

Linfeng Sui[1], Xuyang Zhao[2], Jianting Cao[3], Qibin Zhao[4]

Abstract - Epileptic focus localization is plays a key role for successful surgical therapy of resection of epileptogenic tissues. However, manual diagnosis of intracranial electroencephalogram (iEEG) signals by highly skilled clinicians are arduous and time-consuming. In contrast, the focus can be localized by classifying of focal and non-focal iEEG signals, which can improve the accuracy and shorten the time to diagnosis. In this paper, we propose a mixed 1-D & 2-D convolutional neural networks (CNN) model which is inspired by recent developments from the field of image classification and attempt to improve the classification accuracy of iEEG signals. We apply our approach to the Bern-Barcelona iEEG dataset for evaluating the performance. Our model directly takes time-series iEEG as input and classifies the iEEG signals without requiring any feature extraction. Experimental results show that our approach is able to differentiate the focal from non- focal iEEG signals with an average classification accuracy of 92.8%.
Keywords - Epilepsy, Focus localization, CNN, iEEG

1. INTRODUCTION

EPILEPSY is one of the most common neurological diseases globally, according to the World Health Organization (WHO), approximately 50 million people suffer from it worldwide [1]. Epilepsy is a chronic disorder of the brain and is characterized by recurrent and unpredictable seizures which are caused by the uncontrolled electrical discharges in a group of brain neurons. Recent studies have shown that up to 70% of patients could become seizure-free with appropriate use of anti-seizure medicines (AEDs) [1]. For patients with drug-resistant focal epilepsy, resection of epileptogenic tissues is one of the most promising treatments in controlling epileptic seizures. Hence, it’s important to determine the seizure area in surgical therapy.

iEEG which measures brain activity through the recording of electrical activity from the cerebral cortex and has been widely used for the diagnosis and management of various neurological conditions such as epilepsy, brain death, Alzheimer's, and coma. iEEG is enabling to be used for identification of seizure focus due to the nature that focal iEEG signal is more stationary and less random than non-focal iEEG signal [2]. As it is uncertain that symptoms will present in the iEEG signal at all times, long-term interictal iEEG should be monitored and recorded from epilepsy patients. Large amounts of data are generated in this process that subsequently needs to be manually interpreted with visual inspection by experienced neurological clinicians to detect the seizure area. That can cause a delay in the patient’s course of treatment since the inspection works cost much time. There- fore, the method of automatic detection of epileptic focus is necessary.

Many methods of automatic detection have been proposed to improve the efficiency of clinicians by accelerating the reading process and thereby reducing workload, such as classification of normal, interictal and seizure [3] [4]. For drug-resistant focal epilepsy, in order to determine the epileptic seizure focus according to the iEEG signals, it is essential to extract the most discriminative features and then to classify those features into the focal part or non-focal part.

The most common sequential steps in the development process of the method of automatic detection are pre-processing, feature extraction, and classification. In the preprocessing step, normalization and various filtration are applied to the raw signals to standardize the model for the next step. In the feature extraction step, the distinctive signatures present in the iEEG signals are extracted by various methods. The commonly used feature extractors are entropy, empirical mode decomposition (EMD) [5] and time-frequency analysis such as Fourier transform (FT) [6], wavelet transforms (WT) [7] [8], Hilbert-Huang transform [9], short time Fourier transform (STFT) [10], etc. In the classification step, the classifiers, including support vector machines (SVM) [5], K-Nearest-Neighbor method (KNN) [11] and neural networks such as CNN [12] and recurrent neural network (RNN) [13] are widely used for the classification of features obtained by feature-extraction methods manually.

In this paper, inspired by successes in 1D-CNN with the raw iEEG time-series (for simplicity, we call it 1D-CNN and 2D-CNN with features extracted from the time-frequency domain with the use of STFT (TFCNN). We propose a mixed 1D-2D convolutions model, in which 1D convolution layers are used to preliminary feature extraction, then the feature maps are

[1] Department of Electronic Engineering, Saitama Institute of Technology, Fukaya, Japan
[2] Department of Electronic Engineering, Saitama Institute of Technology, Fukaya, Tensor Learning Unit, RIKEN Center for Advanced Intelligence Project, Tokyo, Japan
[3] Department of Electronic Engineering, Saitama Institute of Technology, Fukaya, Japan
[4] Tensor Learning Unit, RIKEN Center for Advanced Intelligence Project, Tokyo, Japan, School of Automation, Guangdong University of Technology, Guangzhou, China

reshaped and fed to 2D convolution layers to further feature extraction, the final feature maps from these layers are flattened and then fed to a fully connected neural network. We name this model MCNN.

The rest of the article is organized as follows: Section II describes the method of 1D-CNN and STFT. Section III describes the architecture of 1D-CNN, TFCNN and MCNN model. Section IV describes the dataset which is used in experimental. The experimental results are presented in Section V and the last is the conclusion of this study.

2. METHODS

CNN is a subset of deep learning which has recently been successfully used in the task of time series classification, such as EEG signal, Electrocardiography (ECG) and speech. In this section, we first describe the working principle of CNN architecture and various neural network components used in this study. Then we discuss the STFT, a method of time-frequency domain feature extraction. This collection of principles and components provides a critical basis for the three CNN model proposed in Section III.

Convolutional Neural Network

In the CNN model, the early layers following input layers are convolutional layers. In convolutional layers, the convolution operation is applied to extract feature maps from the input file of the previous layer, One-dimension convolutional layer: It consists of one-dimension learnable filters which slide across one-dimension input file like time series. Two-dimension convolutional layer: A two-dimension filter is convolved across the width and height of the input file like images. The activation map is obtained by computing the dot product of the input file and the filter. Then after additive bias and non-linear map by activation functions, feature maps of the convolutional layer are outputted to passed to the next layer in the CNN model. Pooling Layer: In the pooling layer, feature maps from the upper layer are down-sampled to reduce the size, lower the calculation complexity and prevent overfitting. In CNN, the pooling layer is a common down-sampling method that the feature maps are separated into many rectangle regions, and then each region features are obtained. Pooling operation various, for instance, max-pooling operation selects only the maximum value in each region, while mean-pooling obtains the mean value of each region. Pooling is the expression of local features and consequently reduces the dimension. Batch Normalization Layer: Batch normalization layer is applied to normalizes the output of the previous layer by subtracting batch mean and dividing by batch standard deviation, to fight the internal covariate shift problem and increase the stability of a neural network.

For the input x obtain from the previous layer, the batch normalization layer first calculates the mean μB and variance σB2 of a mini-batch B of size m by (1) and (2). Then normalized values $\overline{x}$i are calculated as (3) where ε is a constant added to the mini-batch variance for numerical stability. Finally, the $\overline{x}$i is shifted and scaled as (4) that the parameters γ and β are to be learned [14].

$$\mu_{\mathcal{B}} = \frac{1}{m}\sum_{i=1}^{m} x_i \tag{1}$$

$$\sigma_{\mathcal{B}}^2 = \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \tag{2}$$

$$\overline{x_i} = \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \tag{3}$$

$$y_i = \gamma \overline{x_i} + \beta \tag{4}$$

2.1 Short time Fourier transform

On account of the instability of the iEEG signal, it is extremely difficult to extract the key features by some commonly time-frequency analysis methods such as Fourier transform, nevertheless, it is demonstrated that the time-frequency domain extracted by STFT is suitable for classifying EEG signal of epilepsy. For STFT, the process is to divide the signal into some shorter segments equally so that the signal is approximately stationary, and then use the Fourier transform to compute the spectrum of each shorter segment [15]. For a determined signal x(t), the time-frequency domain at each time point can be obtained by the following (5).

$$STFT\{x(t)\}(\tau, \omega) = \int_{-\infty}^{\infty} x(t) w(t-\tau) e^{-j\omega t} \, dt \tag{5}$$

where w(t) is the Hann window function centered around zero. Examples of the spectrogram of iEEG signals (focal and non-focal) are shown in Fig. 1.

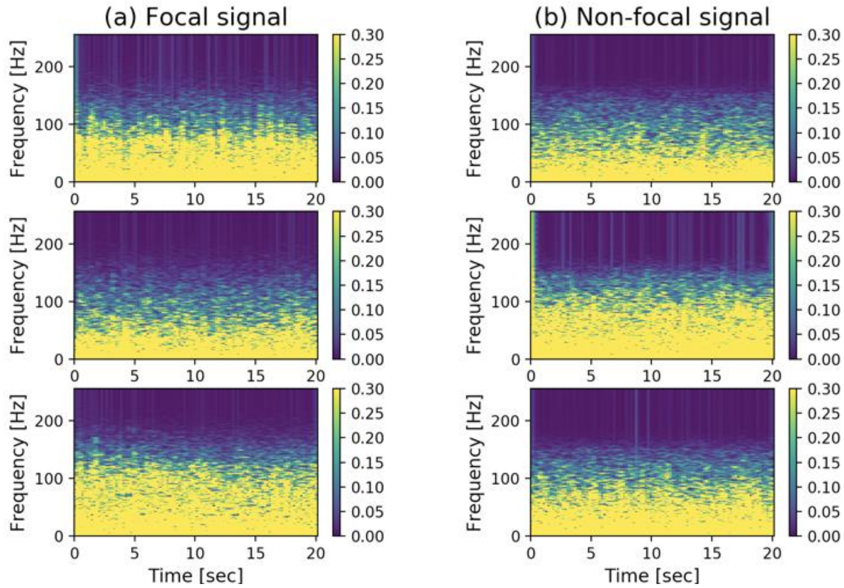

Figure 1 STFT of focal and non-focal iEEG signals

3. NEURAL NETWORKS ARCHITECTURE

3.1. One-dimension Convolutional Neural Network

The developed one-dimension convolutional neural network architecture has 27 layers consist of the input, one-dimension convolution, max-pooling, dropout, batch normalization, and fully connected layers. The architecture of 1D-CNN is shown as Fig. 2 (a). The convolution layers following the input layer, perform the convolution operation on the input raw iEEG signals. The size of the filter and stride are set as three and two, respectively. Feature maps obtained from the previous convolution process are then successively processed by the max-pooling layer and batch normalization layer. Before fed into the fully connected layers, feature maps are flattened to transform dimensions. The sigmoid layer is used in the last layer of the architecture to execute the classification process. In this layer, the input EEG signals are classified as focal or non-focal.

3.2. Time Frequency Convolutional Neural Network

In our previous research, we proposed an architecture that combines time-frequency analysis and a two-dimension convolutional neural network. The architecture of TFCNN is shown as Fig. 2 (b). In that architecture, the iEEG signals are firstly transformed by STFT to extract local features individually based on the local correlation among the time-frequency domain. Then discriminative features which are built by connecting the local features are learned and classification is performed by the TFCNN. The specific training process is as follows: The Time-frequency spectrogram is firstly convoluted by a 3×3 filter by sliding with stride 1 and set 10 channels to feature map, each feature map has the same size as the input spectrogram. Then normalization and max-pooling operation are successively implemented in the batch normalization layer and max-pooling layer. And these two steps are repeated five times, except that the size of input and output are decided by the former layer, and channels of the feature map increase exponentially. Similar to the 1D-CNN, the last step of TFCNN also executes the classification process.

3.3. Mixed Convolutional Neural Network

In the previous TFCNN architecture, before feeding into the neural network the signals need to perform extraction and selection of features manually. The most used time-frequency analysis method like STFT has the capability to extract local information at a one-time scale determined by a single filter, limiting the flexibility of the model. To address this problem, we propose a mixed 1D-2D convolutions model, instead of STFT, we select to setting one-dimension convolution in the earlier layers, because it is easier to optimize the parameter configuration when each layer is treated independently, and it also enables using different input feature maps or receptive field sizes. The architecture of MCNN is shown as Fig. 2 (c). The feature maps from one-dimension convolution layers are reshaped and then successively fed to two-dimension convolution layers and fully connected layer to perform further feature extraction and classification.

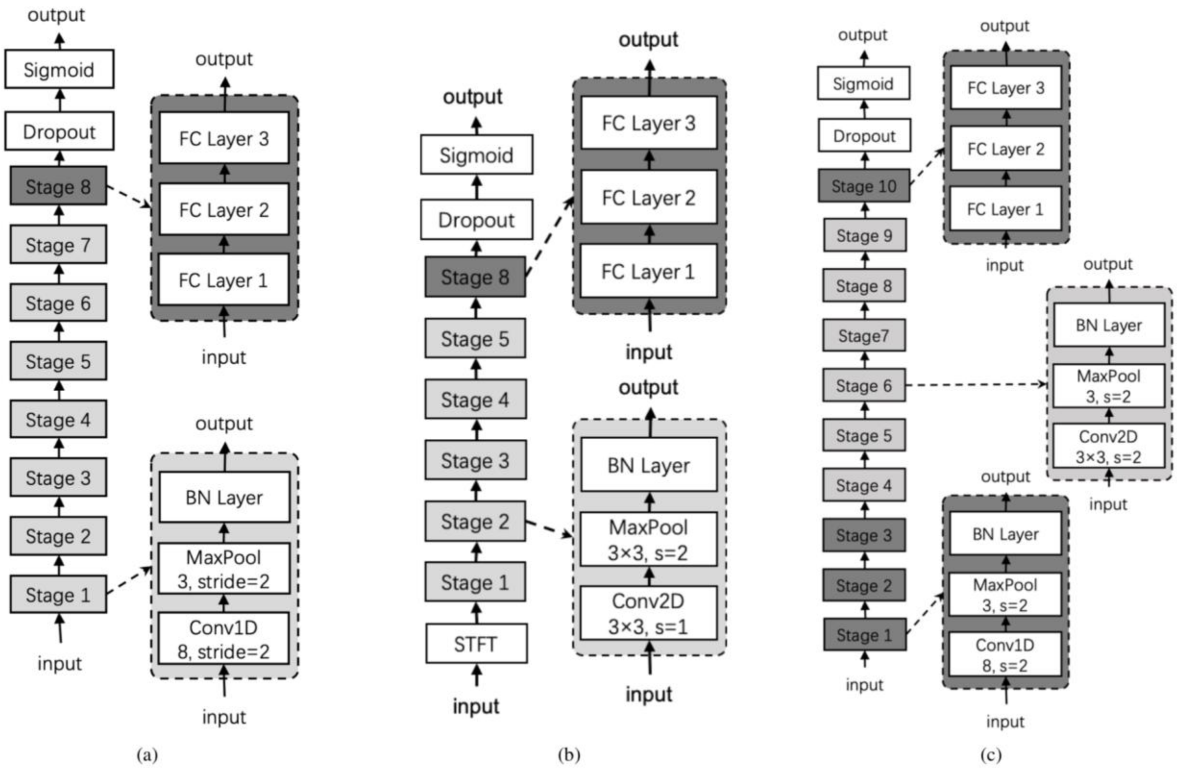

Figure 2 An overview of architectures of 1D-CNN, TFCNN, MCNN proposed

4. DATASET

The iEEG signals used in this paper were obtained from the publicly available Bern-Barcelona iEEG dataset, it were collected by Andrzejak et al. at the Department of Neurology of the University from five patients suffering from long-standing drug-resistant temporal lobe epilepsy and were candidates for surgery [2]. The dataset contains 3750 focal iEEG signals pairs and 3750 non-focal iEEG signals pairs, each pair of iEEG signals were recorded from adjacent channels. Signal recorded at the epileptogenic region was labeled as the focal signal, otherwise, it was labeled as the non-focal signal. The iEEG signals were sampled of 20 seconds at a frequency of 512 Hz and then band-pass filtered by a fourth-order Butterworth filter between 0.5 and 150 Hz. The iEEG signals recorded during the seizure and three hours after a seizure last time were excluded to guarantee to eliminate the seizure iEEG signals. An example of the focal and non-focal iEEG signals is shown in Fig. 3, respectively.

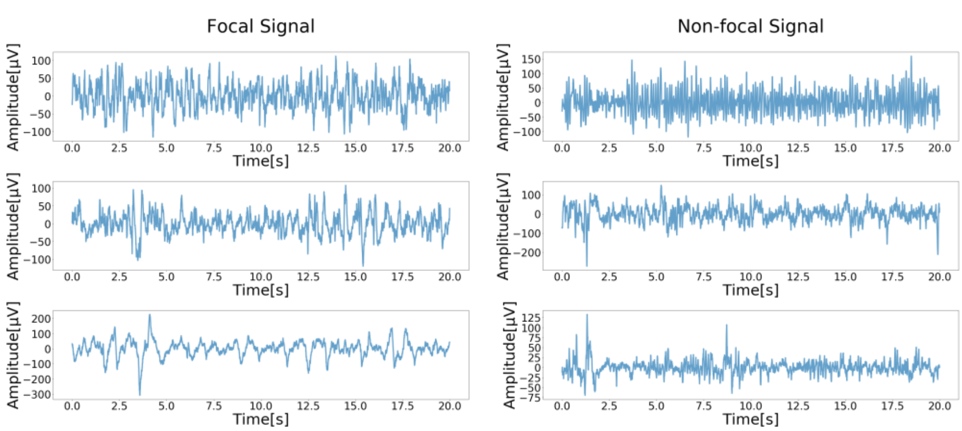

Figure 3 Example of the focal and non-focal iEEG signals

5. EXPERIMENTAL RESULT AND DISCUSSION

Bern Barcelona iEEG dataset has been used to evaluate our proposed models. 80% of the dataset is used as the training set, 10% is used as a validation set while the remaining 10% is used as the test set. In the training stage, the network has been trained to recognize two classes of iEEG signals of focal and non-focal signals. It requires a large number of computational overhead to use one iteration of the full training set to perform each epoch, hence stochastic gradient descent (SGD) training is used in this paper. In each epoch of the training, the 12000 data are randomly divided into 100 batches, which are fed into the network in turn. Training performance was monitored during the training stage until getting the best accuracy on the training set with minimum train loss. And we validate the networks by using the validation set after each epoch of training. The accuracy of the validation set across classification by the different models is shown in Fig. 4. The average confusion matrix obtained through 10-folds cross-validation is shown in Table 1. Compare with other state-of-the-art method records in Table 2, our model of MCNN obtained 92.8% accuracy.

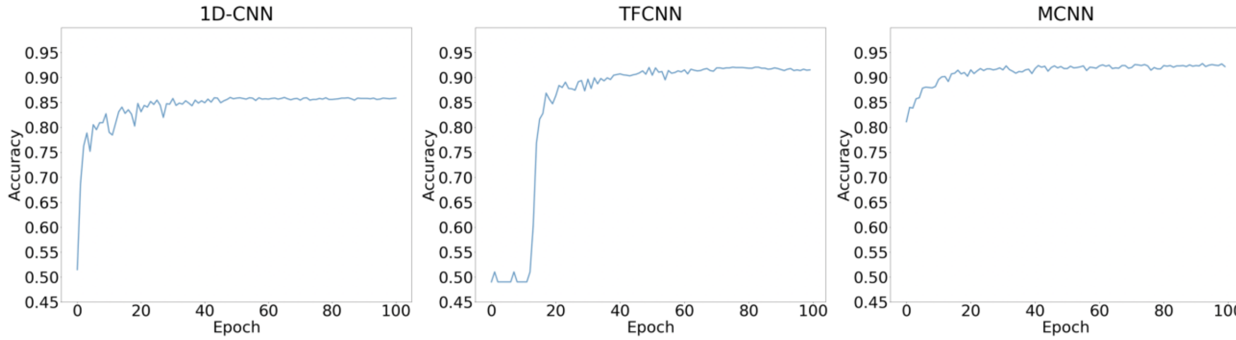

Figure 4 The accuracy of the validation set on 1D-CNN, TFCNN, MCNN

Table - 1 Experiment Result

a) 1D-CNN model

	Focal (Predict)	Non-focal (Predict)
Focal (True)	628	119
Non-focal (True)	115	638
Precision (%)	Recall (%)	Accuracy (%)
84.5	84.1	84.4

b) TFCNN model

	Focal (Predict)	Non-focal (Predict)
Focal (True)	686	164
Non-focal (True)	56	694
Precision (%)	Recall (%)	Accuracy (%)
92.4	91.4	92.0

c) MCNN model

	Focal (Predict)	Non-focal (Predict)
Focal (True)	687	52
Non-focal (True)	56	705
Precision (%)	Recall (%)	Accuracy (%)
92.5	93.0	92.8

Table - 2 Experiment Result

Article	Method proposed	Performance (%)
[16]	DWT, SVM	83.07
[17]	EMD, Entropy, LS-SVM	87
[18]	EMD-DWT, Entropy, KNN	89.4
[19]	DWT, Entropy, LS-SVM	84
[11]	TQWT, Entropy, LS-SVM	84.67
[5]	BEMD, SVM	86.89
MCNN	1D & 2D CNN	92.8

6. CONCLUSION

Since it is time-consuming to inspect iEEG by manual visual, automates the detection of epileptic focus by an effective classifier will have the potential to reduce delays in treatment. In this paper, we present and compare the performance of three different models (1D-CNN, TFCNN, MCNN) for iEEG signals classification as focal and non-focal iEEG signals. The MCNN achieves the best accuracy rate in three models, and the advantage of this model is that it is an end-to-end model in which separate steps of feature extraction and feature selection are not required in this work. The results with 92.8% accuracy demonstrate that this method is effective with much efficient and time-saving to assist neurological clinicians to diagnose the focal epileptic seizure area.

7. ACKNOWLEDGMENTS
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